PROCEEDINGS
OF THE
THIRTEENTH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

THURSDAY SESSIONS
VOLUME II

The Impact of Learning Curve Model Selection and Criteria for Cost Estimation Accuracy in the DoD

Candice Honious, Student, Air Force Institute of Technology
Brandon Johnson, Student, Air Force Institute of Technology
John Elshaw, Assistant Professor of Systems Engineering, Air Force Institute of Technology
Adedeji Badiru, Dean, Graduate School of Engineering and Management, Air Force Institute of Technology

Published April 30, 2016

ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF BUSINESS & PUBLIC POLICY
NAVAL POSTGRADUATE SCHOOL

Panel 21. Methods for Improving Cost Estimates for Defense Acquisition Projects

Thursday, May 5, 2016	

3:30 p.m. – 5:00 p.m.	**Chair: Major General Casey Blake, USAF,** Deputy Assistant Secretary for Contracting, Office of the Assistant Secretary of the Air Force (Acquisition)
	
	 The Role of Inflation and Price Escalation Adjustments in Properly Estimating Program Costs: F-35 Case Study
	    Stanley Horowitz, Assistant Division Director, Institute for Defense Analyses
	    Bruce Harmon, Research Staff Member, Institute for Defense Analyses
	
	 The Impact of Learning Curve Model Selection and Criteria for Cost Estimation Accuracy in the DoD
	    Candice Honious, Student, Air Force Institute of Technology
	    Brandon Johnson, Student, Air Force Institute of Technology
	    John Elshaw, Assistant Professor of Systems Engineering, Air Force Institute of Technology
	    Adedeji Badiru, Dean, Graduate School of Engineering and Management, Air Force Institute of Technology
	
	 Cost and Price Collaboration
	    Venkat Rao, Professor, Defense Acquisition University
	    David Holm, Director, Cost and Systems Analysis, TACOM LCMC
	    Patrick Watkins, Chief, Stryker/Armaments Pricing Group, Army Contracting Command

The Impact of Learning Curve Model Selection and Criteria for Cost Estimation Accuracy in the DoD

Candice M. Honious—is the EMD Cost Analyst for the Combat Rescue Helicopter program at Wright-Patterson Air Force Base in Dayton, OH. She received her master's degree in cost analysis from the Air Force Institute of Technology and a bachelor's and master's degree in accountancy from Wright State University in Dayton, OH. [candice.honious@us.af.mil]

Captain Brandon J. Johnson—is a Weapons Systems Cost Analysist at Wright-Patterson Air Force Base in Dayton, OH. He received his master's degree in cost analysis from the Air Force Institute of Technology, as well as a Master of Business Administration from Oklahoma State University and a bachelor's degree from the United States Air Force Academy. [brandon.johnson@afit.edu]

John J. Elshaw—is an Assistant Professor of Systems Engineering in the Department of Systems Engineering and Management at the Air Force Institute of Technology. He holds a BS in accounting from The University of Akron, an MBA from Regis University, and a PhD in management with a specialization in organizational behavior and human resource management from Purdue University. [john.elshaw@afit.edu]

Adedeji B. Badiru—is a Professor of Systems Engineering at the Air Force Institute of Technology. He is a registered Professional Engineer (PE), a certified Project Management Professional (PMP), and a Fellow of the Institute of Industrial Engineers. [adedeji.badiru@afit.edu]

Abstract

The first part of this manuscript examines the impact of configuration changes to the learning curve when implemented during production. This research is a study on the impact to the learning curve slope when production is continuous but a configuration change occurs. Analysis discovered the learning curve slope after a configuration change is different from the stable learning curve slope pre-configuration change. The newly configured units were statistically different from previous units. This supports that the new configuration should be estimated with a new learning curve equation. The research also discovered the post-configuration slope is always steeper than the stable learning slope. Secondly, this research investigates flattening effects at tail of production. Analysis compares the conventional and contemporary learning curve models in order to determine if there is a more accurate learning model. Results in this are inconclusive. Examining models that incorporate automation was important, as technology and machinery play a larger role in production. Conventional models appear to be most accurate, although a trend for all models appeared. The trend supports that the conventional curve was accurate early in production and the contemporary models were more accurate later in production.

Introduction

The Budget Control Act of 2011 subjected the Department of Defense (DoD) to a more fiscally constrained and financially conscious environment than ever before, juxtaposed with a demand for new aircraft programs of almost every type. As an increasing number of programs are terminated, with budget overruns being a contributing factor, managers at every level in the DoD are expected to ensure the Department's shrinking budget is being used in the most effective way. The increased scrutiny adds greater emphasis on the accuracy of program office cost estimates given that an approved program cost estimate supports every major aircraft acquisition program funded by the Department.

The current state of the DoD includes shrinking budgets and large funding cuts for acquisition programs. An extra emphasis on scrutiny of accurate cost estimates is the result of the current cuts and budget issues. There is a new standard for Financial Managers and Program Managers who have to support and maintain a cost estimate like no time before.

Having a balanced budget is a concern for the DoD, and the budget depends on the cost estimate. Gone are the days when the DoD had ever-growing budgets where the fiscal mentality was to spend. The fiscal mentality now involves saving and receiving as much value as possible for every budgeted dollar.

In order to obtain reliable cost estimates, cost estimating models and tools within the DoD present the opportunity for an evaluation on their accuracy. The current learning curve methods within the DoD's cost estimating procedures are from the 1930s. As automation and robotics increasingly replace human touch-labor in the production process, a model that is 80 years old and assumes constant learning may no longer be appropriate for accurate learning curve estimates. Robotics and automation do not learn, and they are inevitably a part of future production. New learning curve methods that consider automated production should be examined as a possible tool for cost estimators to utilize. The modern learning curve methods could be a useful tool for obtaining better cost estimates within the DoD. The purpose of this research ultimately is to investigate new learning curve methods, develop the learning curve theory within the DoD, and pursue a more accurate cost estimation model.

A vital input to the cost estimate for a production program is the assumed learning curve slope for the program. The learning curve often depicts the learning phenomenon that occurs in manufacturing. Learning is defined as a constant percentage reduction of the required touch labor hours (or costs) to produce an individual unit as the quantity of units produced doubles (Yelle, 1979, p. 302)—as the number of units produced doubles, the number of hours required to produce a single unit decreases by the learning curve rate. Learning is also defined as both the conceptual and the physical learning of a physical process (Watkins, 2001, p. 18). The learning curve for a program is generally considered stable once the program is substantially into production because the manufacturer and laborers have produced enough units to learn the most efficient production process. However, intuitively and through past research, it is known that learning is disrupted by changes in production, and only the production of additional units can recover the lost learning (Watkins, 2001, p. 18). It is critical to capture the change in the learning rate due to production modifications to better estimate DoD program costs.

This comparative analysis study will examine whether different learning curve models are more accurate than Wright's Learning Curve model (the status quo) when comparing actual values to predicted. The current DoD learning curve methodology does not take into account available information and factors that contribute to learning. The point of emphasis for this research and the issue that needs to be resolved is that DoD agencies need to estimate more accurately. Prior research on this subject shows that the learning curve methods have room for further development. There may be an opportunity to incorporate alternate learning curve models and more DoD programs into this area of research. Research found that an important factor (incompressibility) was not explicitly researched or known. Towill and Cherrington defined incompressibility as the percentage of the learning process that is automated (Towill, 1990). Robotics and automation are not going away and will likely play a larger role in the future. Research on what that factor actually equals or how it relates to different airframes could be critical for obtaining a more precise model. Using integration, assembly, and checkout (IA&CO) processes instead of complete touch labor processes should provide an analysis that is more insightful and potentially leads to a more accurate model. IA&CO are specific work that occurs during production.

The idea of learning in a production environment is well established. T.P. Wright first published the learning curve phenomenon in early 1936. Wright observed that in a

manufacturing environment, as the cumulative quantity of units produced doubled, the cumulative average cost decreased at a constant rate (Wright, 1936, pp. 124–125; Yelle, 1979, p. 302). During World War II, government contractors investigated the usefulness of the learning curve concept to predict labor hours and cost requirements for aircraft and ship construction projects. The private sector went on to adopt the learning curve theory into practice shortly thereafter. Although learning curve theory has evolved and has been referred to by different names in the decades following Wright's report, including the experience curve, the progress curve, and the improvement curve, Wright's model remains one of the models most widely used by manufacturers to predict labor hours and costs (Yelle, 1979, pp. 303–304; Badiru, 1992, p. 176.).

Wright's original findings postulated a constant learning environment; however, researchers have not ignored the idea that constant learning may not exist on a continual basis in a manufacturing environment. In fact, the ideas of regressed and lost learning have been widely studied. Research studies support that a break in production creates an environment of relearning because the labor resources have stopped working, at least on the same project, and will be less efficient at manufacturing when production restarts (Anderlohr, 1969, pp. 16–17).

In addition to production breaks, instances also exist when a major configuration change occurs during production and disrupts the learning process. In this situation, the new configuration is immediately incorporated into the next units on the production line; the units already produced are retrofitted at a later time. Intuitively, the units with the configuration change should initially have a different learning rate than the units without a change because the manufacturers must learn how to incorporate the change into the production process. However, because the learning rate for the new configuration is unknown, DoD program offices generally do not treat the reconfigured units with a different learning rate. As a result, the program often experiences substantially different hours/costs for the newly configured production units than their original learning curve projected. A configuration change in a production program does necessitate learning for the contractor, and the impact to learning attributable to the configuration change should be understood by all levels of the DoD acquisition community. Wright (1936) understood this limitation to the learning curve theory application even in the infancy of the idea:

> The tremendous cost of changes introduced into a production order during construction is too well known to require emphasis. This cost is involved, not only in shop delays, but in the engineering expense of re-designing. It is appreciated that in a rapidly moving art such as aviation, changes are more or less inherent. … In using the curve developed in this paper, it should be recognized that the factors derived are based on the assumption *that no major changes will be introduced during construction*. (Wright, 1936, p. 124)

One of the first and most recognizable learning curve formulas is y= ⟦ax⟧ ^b. This is referred to as the Unit Learning Curve Model,

$$y = ⟦ax⟧\ ^b \tag{1}$$

where

y = the estimated production hours or cost

a = the production hours of the theoretical first unit

x = is the unit produced

b = is a factor of the learning = log R (learning rate)/log2

The Air Force methodology on learning curves and guidance in their application is found in Chapter 8 of the *Air Force Cost Analysis Handbook* (AFCAH) and Chapter 17 of the DoD Basic Cost Estimating Guidebook (BCE). These two guides focus on two theories: unit theory and cumulative average theory. The unit theory, Equation 1, predicts a specific unit cost. Cumulative average theory focuses on the average of all units produced up to a certain point in the production process. The cumulative average and unit theory have been the standard in manufacturing. However, research has shown other models may provide a more accurate predictor of cost.

Study 1: Production Break and Lost Learning

Current DoD program office cost estimating assumes a stable rate of learning once a program is substantially into production. However, intuitively, a configuration change introduced into the production line will initially disrupt the learning effect. This study will research two main questions to address the implications when a configuration change occurs during production:

1. Is there an impact to the learning curve slope when a configuration change is introduced to the production line? Specifically,
   a. What is the learning curve slope for each new configuration;
   b. Are the production segments for each configuration significantly different; and
   c. What is the difference between the hours predicted based on the prior configuration and actual hours for each segment?
2. How many units of the newly configured aircraft are produced before the contractor recovers the stable learning rate?

The first research question leads to a single testable hypothesis to determine if the mean amount of labor hours prior to a configuration change is the same as the mean amount of labor hours subsequent to a production change?

Hypothesis 1:

H_0: Mean labor hours $_{\text{prior to configuration change}}$ = Mean labor hours $_{\text{post configuration change}}$

H_a: Mean labor hours $_{\text{prior to configuration change}}$ ≠ Mean labor hours $_{\text{post configuration change}}$

If the analysis results fail to reject the null hypothesis, this would indicate that the data points come from the same population and a configuration change did not have a significant impact to the learning during production. If the analysis rejects the null hypothesis, this would indicate the opposite, that the data points representing different configurations come from different populations and that a configuration change did have a significant impact to the learning during production. If the results support rejecting the null hypothesis, using the prior learning curve equation is inappropriate to predict the hours of the new configuration because the units come from different populations. The second research question does not require a hypothesis test.

Production Break and Lost Learning

As the learning curve theory has evolved, researchers and practitioners have investigated the impact to the learning rate when other than constant production exists. George Anderlohr (1969) is credited with developing a model to determine the additional hours/costs that result from a break in production. Anderlohr (1969) defined a production break as "the time lapse between completion of a contract for the manufacture of certain

units of equipment and the commencement of a follow-on order for identical units" (p. 16). A break in production results in increased hours and costs because the laborers are no longer performing their tasks on a constant repetitive basis and the laborers become less efficient (have a loss of learning) during the production break timeframe (Anderlohr, 1969, pp. 16–17).

Studies have also discovered that lost learning can be a result of forgetting at times other than during a production break (which is considered scheduled forgetting). Two other instances when forgetting can occur are (1) at random due to the inability to continue work (e.g., machine breakdowns), and (2) based on a natural process (e.g., aging workforce; Badiru, 1995, p. 780). Badiru goes on to conclude that "whenever interruption occurs in the learning process, it results in some forgetting." The amount of forgetting is a function of both the length of disruption and the initial performance level (Badiru, 1995, p. 780).

Additional Work Theory

A similar circumstance to the production break theory that has a similar result is the idea of new learning, when manufacturing is interrupted with a major configuration change to the production unit. When the unit being manufactured is changed, the laborers must adjust their processes to learn how to correctly produce the newly configured unit. Historically, adjusting the learning curve to account for the impact due to configuration changes is referred to as splicing or splitting the curve, although little research has been done in this area with empirical data. The theory of splitting the curve provides rationale to split the curve between units of different configurations (pre- and post-configuration change) because the latest production unit usually provides the greatest estimate for future production units (Dahlhaus & Roj, 1967, p. 16).

Sample Data

There were three limiting conditions the data had to satisfy to be included in this study: (1) at least one identified configuration change must come into the production line during production, (2) all units must be produced on the same production line, and (3) the program must be "substantially" into production. For the purposes of this analysis, substantially into production is defined as those units considered by the program office to be representative of stable production and exclude any units identified as developmental or pre-production.

After excluding programs that did not meet the research conditions, there were four data sets available at the time of the analysis, including one joint service and three Air Force aircraft programs. Due to the proprietary nature of the production data, the program names are not disclosed and will be identified as Programs A, B, C, and D. In addition, three classes of aircraft are represented in this study: Unmanned Air Vehicle, Cargo, and Fighter aircraft.

Analysis Methods and Results

To test the research hypothesis, the data will be split into separate segments at each identified configuration change to identify if the segments are statistically similar based on the mean or median labor hour values. Using the touch labor hours, the learning rate before an identified configuration change and the learning rate after the change will be calculated to address the remaining areas of the first research question. Both calculations will use Crawford's unit theory equation $y = ax^b$; because the data is available in units, a unit analysis is appropriate. In addition, to avoid the smoothing effect and the obfuscation of unit variation a cumulative unit curve can create, the unit learning curve method will provide the most explanatory results of the two methods (unit and cumulative average) for the intent of this study (ICEAA Module 7, 2013, p. 14).

The slope will be calculated each time an identified configuration change occurs and not at other instances, even if a pattern change is evident in the scatter-plot of the data. The learning curve equation of a segment will forecast the touch labor requirements of the successive production segment. The forecasted hours of an identified configuration change will be compared to the actual hours of the same configuration to calculate the difference and the percentage difference.

To answer the second research question, an analysis will determine the number of aircraft produced after a configuration change until the prime contractor was able to return to a stable learning rate. This will be accomplished by removing one production unit at a time (in sequential order beginning with the first unit of the segment) and calculating the learning curve slope of the remaining units until the stable rate of the prior segment is achieved. An overall commonality is not expected because every program, every contractor, and the associated production process are different. Instead, the results are informational and may support contract negotiation efforts with more insight into post-configuration change production.

Table 1 includes the slope calculations for each program for each segment identified. Configuration A is always the initial configuration, prior to any changes. Based on this summary, the slope never remained the same after a configuration change. Program C and Configuration C of Program B were excluded from the analysis at this point based on the inappropriateness of the analysis method displayed through scatter-plots in both unit and log space.

Table 1. Segment Learning Curve Slope Values

		Configuration					
		A	B	C	D	E	F
Program	A	63.26%	49.84%	-	-	-	-
	B	87.02%	84.33%	-	-	-	-
	D	91.96%	73.15%	59.04%	68.56%	75.24%	82.49%

In nearly every case involved in this study, the segmented data are statistically different when compared to an adjacent segment, which addresses the issue in the first research question (Configurations A and B of Program B were not found to be statistically different). There is a change to the learning curve slope each time a configuration change is introduced, and in every case examined except one, the median labor hours (which are partially a function of the learning curve slope) for the different configurations are statistically different. These findings suggest that using the prior learning curve equation is inappropriate to predict the hours of the new configuration because the units come from different populations.

Further addressing the first set of questions, the learning curve regression equation for each segment is used to predict the touch labor hours for each unit in the following segment. The total predicted hours for each segment are compared to the total actual hours of the segment, and the results are shown as a difference in hours as well as a percent difference for comparison between the programs. A negative value indicates the estimate was lower than the actuals. Table 2 details the results of the predicted and actual hour comparisons.

Table 2. Learning Curve Equation Prediction vs. Actuals Summary

	Predicted Hours	Actual Hours	Difference	% Difference
Program A				
A predicting B	11,336,756.40	11,371,252.00	(34,495.60)	-0.30%
Program B				
A predicting B*	229,114.62	295,348.35	(66,233.73)	-22.43%
Program D				
A predicting B	1,014,525.48	986,331.30	28,194.18	2.86%
B predicting C	490,909.41	531,988.54	(41,079.13)	-7.72%
C predicting D	339,726.00	368,921.32	(29,195.31)	-7.91%
D predicting E	678,070.58	698,789.63	(20,719.06)	-2.96%
D predicting F	397,530.17	542,429.97	(144,899.80)	-26.71%
*Configuration B not considered a statistically significant change from configuration A				

Given that this portion of the analysis only includes three programs, and two of the programs only compare two segments, there are too few data points to develop any meaningful CER or factor. However, the results are still impactful because for each of the seven segment comparisons, no fewer than 20,000 hours were the difference between the predicted and actuals, which equates to millions of dollars per segment misestimated (generally underestimated) in a cost estimate. Underestimation requires the program office to find dollars not currently in its budget, and overestimation temporarily ties up funding that can be used for other purposes.

In reality, a contractor will submit a tech-refresh proposal to the program office to account for the configuration change, but will estimate the unit costs based on an extrapolation of its stable learning curve because the new slope is unknown. In every program analyzed in this study, the learning curve slope becomes much steeper after the configuration change (when compared to the initial stable slope), and a extrapolation of the stable curve will create a higher per unit cost than the contractor would actually experience with the steeper learning curve. This phenomenon is explored in the next section, which analyzes Program A to answer the second research question of how many production units are manufactured before the contractor returns to its stable learning rate.

Program A was selected for analysis in addressing the second research question because Program A has a large sample size in total and within each segment. In addition, only one configuration change came into the production line, so this program provides a consistent sample to analyze. The stable slope for Program A is 63.26% as determined by the units in Configuration A (units 41 to 71). Table 3 summarizes the slopes for Configuration B beginning with units 72 to 124 and removing one unit at a time from the beginning of the segment until the stable slope was reestablished.

Table 3. Program A Stable Slope Analysis Summary

First Unit	Slope	Units to Stabilize
72	49.84%	
73	50.69%	1
74	51.34%	2
75	51.95%	3
76	52.48%	4
77	52.85%	5
78	52.83%	6
79	52.81%	7
80	53.21%	8
81	53.44%	9
82	53.80%	10
83	54.36%	11
84	54.85%	12
85	55.25%	13
86	56.33%	14
87	57.39%	15
88	59.18%	16
89	60.52%	17
90	62.03%	18
91	63.60%	19
92	64.36%	
93	64.30%	
94	64.52%	
95	63.51%	
96	62.06%	
97	60.54%	

The stable learning rate is achieved with the production of unit 91, which is 19 units after the configuration change came into the production line. While every program will stabilize at different production rates, the important point in this analysis is that after the configuration change is introduced, the contractor learns much quicker on the units after the configuration change than the stable flatter learning rate pre-change. The units immediately following the stabilized rate (92 to 97) are included in the table to show that the contractor does not continue to learn for all units after the stabilized rate is achieved; rather, the contractor's learning rate stays around the stabilized rate. While this analysis is for only one program and cannot be generalized for all programs, the prior analysis did show that for each program, the contractor learned at a much steeper rate following the configuration change. These results provide evidence to support a position other than the contractor extrapolating the prior stable learning curve in a tech-refresh proposal before a configuration change is introduced.

Conclusions of Research

The hypothesis testing indicated a statistically significant difference in the median production touch labor hours in the pre-configuration change and post-configuration change aircraft for every pair of data segments analyzed, except for one. Comparing the median values may equate to a statistically significant difference in the learning curve slopes for those data segments because the impact to the learning curve slope is evaluated through the touch labor hours of the data points, as they are partially a function of the slope value.

The data point analysis to address the stable learning curve research question produced interesting results. The analysis did show a pattern that post-configuration change, the contractor initially learns at a much faster rate and the learning rate decreases with each subsequent unit until the stable learning rate is again achieved. The learning rate did appear to stabilize at this point and did not continue to decrease.

While sample size was limited to a few programs, the results of this study may imply two things. First, that a majority of the time there is an impact to the learning curve slope whenever a configuration change is introduced during production. Second, that the

contractor is able to learn to incorporate the change much more quickly than its stable learning rate for the entire aircraft.

Significance of Research

The results of this research indicate there may be a significant impact to the learning curve slope when a configuration change is introduced during production, even if the program is substantially into production, as were the programs included in this analysis. The findings suggest more research in this area is important for two reasons. First, if more programs are examined, additional data points may lead to the development of a CER or factor to adjust a stable learning curve, which would be a useful tool for cost estimators given the ever-changing acquisition environment. Second, because the learning curve slope is such a crucial factor in production contract negotiations, empirical evidence strengthens the DoD's position of what the contractor's expected learning curve should be—which this study found is not the same as the extrapolation of the contractor's stable learning curve.

An initial estimate that does not anticipate any configuration changes will underestimate unit production hours or costs required for the newly configured unit. If the DoD negotiates a contract based on an extrapolation of the contractor's stable rate, these results provide evidence that the stable rate will overestimate the production requirements; this analysis showed the contractor learns at a steeper rate after a configuration change. The initial underestimating, coupled with the contractor's overestimation, will result in the program office requesting millions of dollars, possibly in excess, per configuration change.

Learning curve theory advises the use of the most recent or most representative production methods to predict the follow-on articles. While this is intuitive and proven to result in better estimates, program offices cannot disregard the prior units. If program offices track the configuration change information and the resulting impacts, the DoD may be in a better position to estimate costs and negotiate production contracts.

Study 2: A Comparative Study of Learning Curve Models

History shows that there is a flattening effect near the end of production runs, learning does not remain constant in aircraft production, and machinery is becoming more involved in the production process. There is evidence to support a hypothesis that a different model may be more accurate than Wright's model. Prior research establishes the foundation for further research into additional types of aircraft. There is evidence to support a hypothesis that a different model may be more accurate than Wright's model. Previous research found that the contemporary models are more accurate than Wright's model given an incompressibility factor (M) that is somewhere between 0.0 and 0.1. M is a number between zero and one where zero indicates a completely manual process and one indicates a fully automated process. Wright's model is the most accurate predictor of cost if M is assumed to be greater than 0.1. Specifically, further research and analysis using program integration, assembly, and checkout. Additional research on the impressibility factor may indicate a model that is more applicable to DoD methodology. For the purpose of this study, the contemporary models examined are the DeJong and S-Curve Models. The following investigative questions are the basis for study 2:

1. How does the application of learning curve models using program integration, assembly, and checkout data affect learning curve models that incorporate an incompressibility factor?
2. How sensitive are IA&CO data to the incompressibility range?
3. Which learning curve model is the most accurate at predicting cost or time?

4. How can the individual airframe work codes prove beneficial for predicting cost or time?

The questions lead to the following hypotheses:

H1: One of the compared models will have Mean Absolute Percent Error significantly different from the others.

H2: One of the modern learning curve models will be significantly more accurate than Wright's model in predicting costs or hours.

H3: The S-Curve model with IA&CO will have a significantly lower MAPE than Wright's and DeJong's Learning Curve Models.

H4: The incompressibility factor will have a significant influence on the accuracy of the DeJong and S-Curve Models.

The first hypothesis' null (H_0) is $\mu_1 = \mu_2 = \mu_3$. This means that the MAPE (lower MAPE is better) for each learning curve model is the same. The alternative hypothesis(H_a) is that one of the model's MAPE is statistically different. A rejection of the null hypothesis in favor of the alternative hypothesis supports significant finding. The significant finding means that testing each contemporary learning curve model against Wright's model is the next phase. The second hypothesis (H2) has a null $\mu_1 = \mu_i$, where i will equal models 2 and 3 (DeJong's and the S-Curve). The H_a is that the contemporary learning curve models will have a lower MAPE than the conventional model$\mu_1 > \mu_i$. H3's null hypothesis is $\mu_2 = \mu_3$. The H_a is that $\mu_2 > \mu_3$, meaning that the S-Curve will have the lowest MAPE and thus be the most accurate predictor of cost or hours. The last hypothesis is that small changes in the incompressibility factor will have a large influence on the MAPE of each model.

Relevant Learning Curve Research

Relevant research has highlighted an important point in why military programs have not adapted a contemporary learning curve model:

Because of the regularity of production in military programs, organizational forgetting, and spillovers of production experience are less apparent. If forgetting is present, it may be very difficult to identify (e. g., data could be consistent with either a 20 percent learning rate or a 25 percent learning rate with 5 percent forgetting). And, in most cases there are not many model variants, so spillovers are not important. (Benkard, 1999, p. 4)

The newest fighter weapon in the U.S. military arsenal will be the F-35. The F-35 has three variants, and the Pentagon plans to spend over $390 billion on these aircraft (Luce, 2014). Five percent of $390 billion attributed to learning/forgetting processes is still a staggering number. The point is that there is room for improvement. Many of the fighter aircraft in use today have had multiple models. The F-15 had models A-E, and the F-16 had models A-F. The DoD can use the hypothesized 5% forgetting to save millions of taxpayers' dollars. The accurate estimates result in less spending, or savings that could go into other taxpayer needs or public works. The estimates enable the DoD to truly forecast budget and spending levels.

One must consider the question of what does the future actually look like in regards to machinery and automation? Are people still going to be relevant for production? In the Defense acquisitions realm, the basis is that with low purchase quantities for state of the art machines will not rely on technological or machine dominated production. This idea really comes down to the machine verses machines argument. Asking whether a robot will take the jobs of humans is key. Experts say yes and no. In the past, machines were used to replace manual labor that was intensive and repetitive. According to a study by the Bank of

America, robots are likely to be performing 45% of manufacturing tasks by 2025, versus 10% today (Madigan, 2011). The price of a computer, a robot, a chip, etc. is falling, and it is speculated that it will fall even more in the future. However, the jobs that require human interaction are least likely to be replaced by a robot. Maybe DoD acquisitions are in the clear and 100% of learning is still realizable for learning curve methodology. Experts agree that the future does include a significant presence of machinery because the prices of robotics and computers are decreasing while the cost of human employees are increasing (Aeppel, 2012).

Contemporary Learning Theory

A contemporary variation of learning curve models is DeJong's Learning Formula. This formula is a modification of Wright's model, and it takes into account the constant, M. M is the incompressibility factor, which is a constant between zero (fully manual operation) and one (fully automated or machine dominated operation; Badiru et al., 2013). Equation 2 highlights DeJong's Learning Model.

$$t_n = t_1\{M + (1 - M)n^{-b} \tag{2}$$

where

t_n = the cumulative average time after producing n units

t_1 = time required to produce theoretical first unit

n = cumulative unit number

b = log R/log 2 (learning index)

M = incompressibility factor (a constant)

A machine based production process would result in no learning, and thus an M value of one. It the basis of this thesis and belief that aircraft production, complex in nature, has an M value close zero because aircraft production is a highly manual process. Thus, M would be closer to zero for IA&CO. M does not have a specific value. This research will focus on the best M value for the particular aircraft production. A potential weakness of the DeJong model is that it does not take into account previous units produced as much as the S-Curve model does.

The S-Curve Model takes into account both previous units produced and the incompressibility factor. Figure 1 shows the effects of learning over time as hypothesized from the S-Curve Model. The linear nature of Wright's original learning curve model has been in question for many years (Everest, 1988). The Rand Corporation first sought to explain the progression of the learning curve used to estimate costs for both military and civilian airframes. The report attempted to describe the relationship between units (quantity) and costs and, ultimately, whether the relationship was linear on a log scale. The results of the Rand Corporation found that a convex curve may provide more accuracy if producing a large number of units (Asher, 1956). The results found that a convex model provides less error if there is a need for large extrapolation. Essentially, an estimation of significantly more units in production instead of fewer provides less error. For units where large extrapolation was required, a non-linear model was more appropriate. The S-Curve model, convex in nature, presents a shape of learning. The S-Curve, when plotted using a log scale relationship, follows an S function. The experience over time (attempts at learning) may exhibit the S-Curve (Everest, 1988).
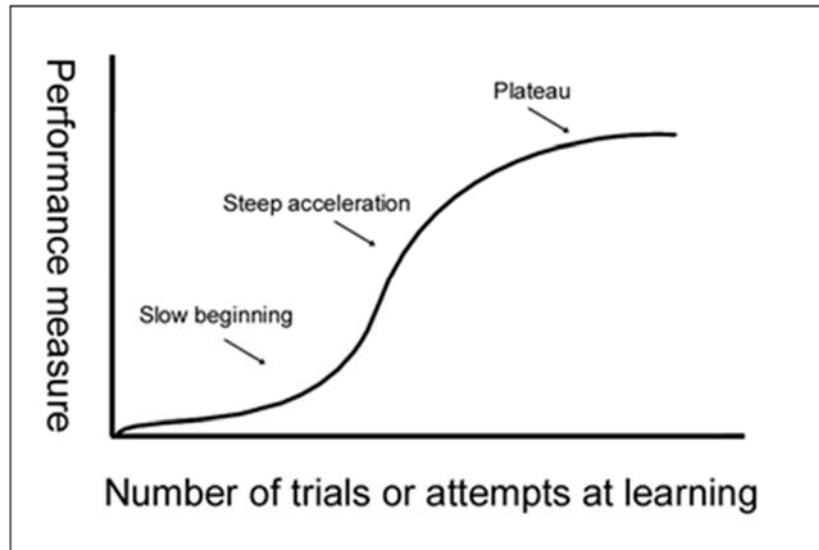
Figure 1.   S-Curve Learning Model

Initially, there is a slow beginning as a worker learns the production process. The newness of the product is a characteristic of the slow initial beginning. New tools, methods, shortages of parts, reworks, and the challenge of developing a cohesive production team are all potential contributors to the slow beginning. The fact that the initial stage in production deals changes from tooling to even workers contributes to the gradual start (Badiru, 1992). From there, learning and familiarity of tools, methods, and workers occur. The learning enables a steep acceleration of production. Production improvement occurs with attempts on the process, or learning by doing. An example from the literature is aircraft production. Aircraft production that includes workers and tools that are more efficient leads to an assembly process that is also more efficient. The efficiencies found result in less time to complete an aircraft (Asher, 1956). However, the improvement and efficiencies eventually begin to fade. The plateau at the trailing edge of the curve is the *slope of diminishing returns* where the curve begins to flatten out, or in many occurrences at the end of production cycles, there is a "tailup" (Everest, 1988). After time, inefficiencies can occur: forgetting, experienced workers focusing on new projects, failure to repair worn tooling at the normal rate, increase of machine disassembly, lack of key materials (safety stock), and workers taking more time to prolong their employment (Everest, 1988). The S-Curve equation is shown in Equation 3:

$$t_n = t_1 + M(n + B)^{-b} \qquad (3)$$

where

t_n= the cumulative average time after producing n units

t_1 = time required to produce theoretical first unit

n = cumulative unit number

b = log R/log 2 (learning index)

M = incompressibility factor (a constant)

B = equivalent experience units (a constant)

From this equation and Figure 1, the forgetting concept is evident. The S-Curve portrays that with time, some inefficiencies will occur. Use of the S-Curve and DeJong

Models may provide more precision to learning curve estimation and enable higher accuracy within DoD cost estimating because they include influences that were previously unaccounted for.

Data

The Air Force Life Cycle Management Center Cost Staff (AFLCMC/FCZ) at Wright-Patterson Air Force Base (WPAFB) provided learning curve data for 17 Major Defense Acquisition Programs (MDAPs). A MDAP is classified as a major program that exceeds a certain dollar threshold. There are 80 MDAPs in the DoD as of 2014. The numbers have decreased slightly over the years. The data files consist of average Learning Curve Reports of Annual Unit Cost (AUC) in addition to the MDAPs estimate methods using Wright's conventional learning curve model. Only one program provided was broken into the specific work codes that include the needed data (IA&CO). When comparing models based on airframe's integration, assembly, and checkout data, the assumption of incompressibility close to zero is acceptable due to the highly individualized process completed by humans.

A description of labor categories Integration, Assembly, and Checkout highlights that not all definitions are synonymous amongst manufacturers. The manufacturers largely consider what is involved in each category as proprietary information. For the purpose of this study, Final Test Integration, Electrical and Mechanical Assembly, Test/Integration, Composites (all locations), and Quality Control are considered IA&CO. Final Test Integration includes the direct labor for the final integration and test, which includes final assembly, system burn-in, payload integration and interface, autopilot checks, taxi tests, range tests and first flight support. Electrical Assembly is the direct labor required to assemble electronic components. Mechanical Assembly is the direct labor required to build servos for the aircraft, to build landing gear, build starter/alternators, to perform rework, and high-time maintenance on those components. Test/Integration is the direct labor for new build electronics, field repairs, integrating avionics, and testing them at the system level. Composites manufacturing is the direct labor required to lay up, cure, and finish components such as the fuselage, wings, tails, and landing gear. Quality Control is the direct labor required to provide inspection of electronics and mechanical components and assemblies, document discrepancies, and resolve problem areas. Of note, these labor categories involve mainly direct labor performed by humans where the learning process is observable. All of the data includes Test Support, Machine Shop, Program Support and Design. These work codes are not repetitive in nature like IA&CO.

Analysis Methods and Results

The data includes actual costs as well as predicted costs using one of the learning curve models. Once calculation of the predicted costs is complete, the error is simply the difference between the actuals costs and the predicted costs. To provide a comparison, a difference calculation in the absolute value and absolute value percent error are the means of analysis. The next step is to perform an analysis to test the hypotheses. ANOVA or the Kruskal-Wallis test will provide the basis for comparing the percent errors. The tests will produce an F-statistic (a test statistic) that falls within a Chi-distribution and a p-value. This comparative study will produce results based on a 95% confidence level (an $\propto$ of 0.05). If the P-value is less than 0.05, rejection of the null hypothesis in favor of the alternative hypothesis will occur. Rejecting the null hypothesis for this study will represent that there is a 95% chance that the tested populations are different. The conditions for ANOVA are as follows: the samples must be from a random selection of the population, normally distributed, and population variances must be equal. If the conditions for ANOVA fail to meet the needed criteria, the Kruskal-Wallis test (non-parametric equivalent to ANOVA) will be the test to determine if multiple samples arise from the same distribution and have the same

parameters ("Kruksal-Wallis Excel," n.d.). The ANOVA or Kruskal-Wallis f-test provides insight into the first hypothesis. The Kruskal-Wallis test is beneficial since the one-way ANOVA is usually robust based on the assumptions for ANOVA. The Kruskal-Wallis test becomes useful in particular when group samples strongly deviate from normal (sample size is small and unequal and data are not symmetric) and variances are different (potential outliers exist). The assumptions for the Kruskal-Wallis test are that no assumptions are made about the underlying distribution; however, assume that all groups have a distribution with the same shape, and no population parameters are estimated (no confidence intervals in the data; Zaiontz, 2015). If the F-statistic is significant, then rejection of the null hypothesis in favor of the alternative that at least one of the sample means is different is the outcome.

The t-Test for two samples test will evaluate the second hypothesis that one or more of the models is a better fit to the data than Wright's Model. The control for this comparison is Wright's Learning Curve Model. Since Wright's Learning Curve Model (WLC) is the control for this study, a comparison to the other model's MAPEs is the method. If the assumption for equal variance is not met, the t-Test for two samples assuming unequal variances will be used. The next analysis that corresponds to H3 will be testing which model is most accurate given significant results for more than one model from H2. Once again, the paired difference t-test is the next step. A paired difference experiment uses a probability distribution when comparing two sample means and produces a t-statistic that falls within a student-t distribution that can either reject or fail to reject the null hypothesis depending on the desired confidence level. Lastly, H4 will require reiterations of the tests in order to determine a good estimate for incompressibility factor based on the airframes. This method will include IA&CO and then all of the data in order to provide a comparison.

Of note, the reader may question why the means cannot provide the basis for the analysis. This lies in the variation of the means. If the coefficient of variation (standard deviation as a percentage of the mean) is low, the mean may be a good predictor of the better model. However, as a rule of thumb, if the coefficient of variation (CV) is greater than 15%, the mean indicates a looser distribution. Most analysts would likely prefer a tighter distribution with less variability. In practice, a low CV (say, 5%) would indicate that the average (mean) of the cost data is a useful description of the data set. On the other hand, if the CV is much higher (say, greater than 15%), there should be a cost driver in the data set that causes the cost to vary. The CVs for the analysis will provide insight into the dispersion of the data points. CVs for the analysis all exceeded the threshold and resulted in the mean not being a good predictor. Table 4 highlights the MAPE analysis for M = 0.05. Results were inconclusive as to which model was more accurate.

Table 4. MAPE Analysis M = 0.05

| WLC	DeJong	S-Curve
4.11%	3.00%	2.64%

A description of the results for the Air Force Program, based on the assumption of low incompressibility values of 0.05 and 0.1, highlights the effects of learning. The results changed between these values and indicated that the S-Curve model may be a more accurate predictor at 0.05, but WLC is more accurate at 0.10. After 0.10, WLC becomes significantly less error prone for both IA&CO and the analysis with all of the work codes. WLC is a better predictor of cost when the incompressibility is 0.10 and higher. Analysis on

all of the data points, not just IA&CO, showed no difference between the models at an M of 0.05. However increasing the M value results in WLC becoming an increasingly more accurate predictor of cost. The following figures highlight the effects of M and the Absolute Percent Errors.
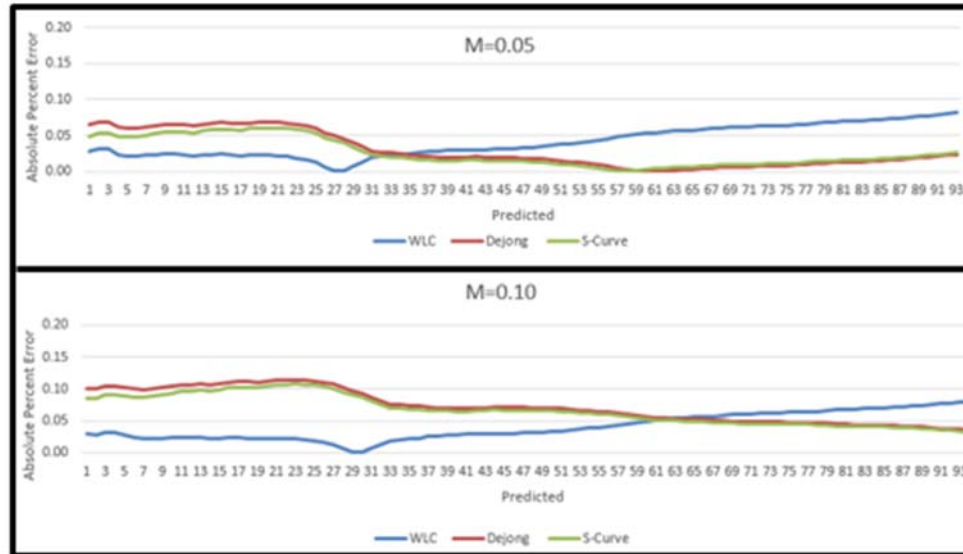
Figure 2.   IA&CO APE Trends

When plotting the Absolute Percent Errors for all of the data points, a trend similar to the analysis using IA&CO was evident. WLC starts as a more accurate predictor of cost and then becomes less and less accurate, whereas the DeJong and S-Curve models become increasingly more accurate predictors. Figure 3 shows the results of APE for all of the data.
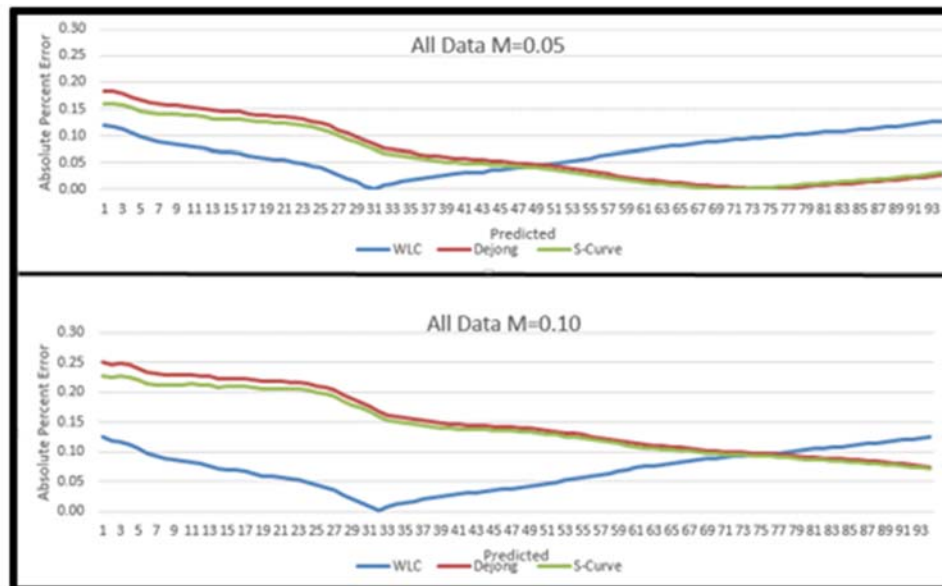
Figure 3.   All Data APE Trends

Conclusions of Research

In summary, results support the first hypothesis that there is a significant difference between the models. Results are inconclusive as to whether any models are significantly more accurate than Wright's model. Between an incompressibility of 0 to 0.1, DeJong and S-Curve models were more accurate (less error prone). Nevertheless, at an incompressibility of 0.10 and beyond, Wright's model is most accurate. The third hypothesis was also inconclusive as to which model is most accurate at an incompressibility of 0.05.

Both DeJong and S-Curve models were more accurate than WLC, but there was no difference between the two. Finally, incompressibility was highly influential as hypothesized. The results of the findings lead to questioning why, for the program chosen, incompressibility would become increasingly more error prone when more automation is present. In addition, the findings put into question how the DoD can draw a conclusion about the application of contemporary learning curve models in acquisitions and specifically cost estimation. Absolute Percent Error figures highlight that WLC is accurate initially and eventually becomes increasingly less accurate. The opposite, S-Curve and DeJong Models are not as accurate initially, but become increasingly accurate over trials. The MAPE analysis averages all of the errors. If the data set included more units, results may trend towards results in favor of the contemporary models. That answer is based on the visual trend from the APE figures. Of interest when the incompressibility factor is 0.10, the models portray that 90% of learning is obtainable. Because the data set was small, changes in incompressibility may not be as evident to the significance of the comparative study.

The findings also put into question how the DoD can draw a conclusion about the application of contemporary learning curve models in acquisitions and specifically cost estimation. If the production cycle is long and many trials will be realized, there is potential that the contemporary models may capture a more accurate picture of learning. Aircraft production may provide starkly different results from a missile production run where more units are produced over time. The results support that there is potential for a more accurate model. However, it may not be in the realm of aircraft production. Aircraft production may include some automation. It is not implausible that aircraft production is 95% manual and supports an M factor of 0.05. The contemporary models may support a more automated process such as a production line much like the automobile industry. Prior studies and subject matter expert opinion support that aircraft production is manual. However, there is a belief that more automation will be present in the future.

Significance of Research

Results from the analysis show that there is reason to believe Wright's Learning Curve may not be the best method for estimating costs. By extrapolating from actuals, the method for Wright's model may not incorporate enough of the variability of learning. The results provide evidence that Wright's Model is accurate initially, but with attempts at learning (trials) the amount of error increases. The comparative analysis on learning curve models provides a standalone analysis of program actuals. The conclusions from this study are that there is potential for a more accurate cost-estimating model and that the conventional learning curve models become increasingly less error prone over trials. The DeJong and S-Curve models show promise as a way to improve DoD cost estimating.

The results of the research do not support all of the hypotheses. Results did confirm that the incompressibility factor was highly influential for both the S-Curve and DeJong models. The results of the comparison changed drastically with a small change in the incompressibility factor. The DeJong and S-Curve models were both more accurate than WLC, but there was no difference between the two. This finding makes it challenging to

simplify the results given the uncertainty of incompressibility. The influence of machinery in longer production cycles is a valid assumption for the future. The influence of automation in this comparative study was evident by the absolute percent error graphs.

References

Anderlohr, G. (1969, September). Determining the cost of production breaks. *Management Review,* 16–19.

Asher, H. (1956). Cost-quantity relationships in the airframe industry. *Project Rand.* Retrieved from http://www.rand.org/content/dam/rand/pubs/reports/2007/R291.pdf

Badiru, A. B. (1992). Computational survey of univariate and multivariate learning curve models. *IEEE Transactions on Engineering Management, 39*(2), 176–188. http://doi.org/10.1109/17.141275

Badiru, A. B. (1995). Multivariate analysis of the effect of learning and forgetting on product quality. *International Journal of Production Research, 33*(3), 777–794.

Daulhaus, F. J., & Roj, J. S. (1967). *Learning curve methodology for cost analysts.* Washington, DC: Department of the Army.

Department of the Air Force. (2007). *Air Force cost estimating handbook.* Washington, DC: Author.

Everest, J. D. (1988). *Measuring losses of learning due to breaks in production* (Master's thesis). Monterey, CA: Naval Postgraduate School.

International Cost Estimating and Analysis Association. (2013). *Cost estimating body of knowledge training, Unit III, Module 7. Learning curve analysis: How to account for cost improvement.*

Kruksal-Wallis Excel. (n.d.). Retrieved December 7, 2015, from https://www.youtube.com/watch?v=KmVTkVnWFuc

Towill, D. R. (1990). Forecasting learning curves. *International Journal of Forecasting, 6*(1), 25–38. http://doi.org/10.1016/0169-2070(90)90095-S

Watkins, P. N. (2001). The persistence of learning and acquisition strategies. *Acquisition Review Quarterly*, 15–30.

Wright, T. P. (1936, February). Factors affecting the cost of *airplanes. Journal of Aeronautical Sciences, 3,* 122–128.

Yelle, L. E. (1979). The learning curve: Historical review and comprehensive survey. *Decision Sciences*, *10*, 302–328.

Zaiontz, C. (2015). Real statistics using Excel. Retrieved from http://www.real-statistics.com/

The Impact of Learning Curve Model Selection and Criteria for Cost Estimation Accuracy in the DoD

Candice M. Honious, USAF

Combat Rescue Helicopter Cost Analyst

Captain Brandon J. Johnson, USAF

MQ-9 Reaper Cost Analyst

Background

- Learning Curve Theory Conception
  - T.P. Wright (1936)
  - J.R. Crawford (1944)

- Learning Curve Theory Evolution
  - S-Model (1946)
  - Stanford-B Model (1956)
  - DeJong Model (1957)
  - Plateau Model (1965)
  - Anderlohr Production Break Theory (1969)
  - Learning/Forgetting/Relearning
  - Additional Work Theory

Research Questions

1. Is there an impact to the learning curve slope when a configuration change is introduced to the production line? Specifically:

   a. What is the learning curve slope for each new configuration?

   b. Are the production segments for each configuration significantly different?

   c. What is the difference between predicted and actual hours for each adjacent segment?

2. How many units of the newly configured aircraft are produced before the contractor regains the stable learning rate?

Methodology

- Segment "stable" production units
  - Visual Analysis
  - Based on identified configuration changes

- Nonparametric Tests
  - Compare actuals between segments to determine statistical similarity

- Regression Analysis
  - Calculate learning curve slope for each segment
  - Compare predicted versus actual hours for adjacent segments
  - Determine number of production units to stabilize rate

Data Analysis

- Regression Analysis
  - Compare predicted versus actuals for each segment pair
  - Negative difference indicates under-estimation

Program A				
	Predicted Hours	Actual Hours	Difference	% Difference
A predicting B	11,336,756.40	11,371,252.00	(34,495.60)	-0.30%
Program B				
	Predicted Hours	Actual Hours	Difference	% Difference
A predicting B*	229,114.62	295,348.35	(66,233.73)	-22.43%
Program D				
	Predicted Hours	Actual Hours	Difference	% Difference
A predicting B	1,014,525.48	986,331.30	28,194.18	2.86%
B predicting C	490,909.41	531,988.54	(41,079.13)	-7.72%
C predicting D	339,726.00	368,921.32	(29,195.31)	-7.91%
D predicting E	678,070.58	698,789.63	(20,719.06)	-2.96%
D predicting F	397,530.17	542,429.97	(144,899.80)	-26.71%
*Configuration B not considered a statistically significant change from configuration A				

1. Is there a significant impact to the learning curve slope when a configuration change is introduced to the production line? Specifically:

   a. What is the learning curve slope for each new configuration?

		Configuration					
		A	B	C	D	E	F
Program	A	63.26%	49.84%	-	-	-	-
	B	87.02%	84.33%	-	-	-	-
	D	91.96%	73.15%	59.04%	68.56%	75.24%	82.49%

   b. Are the segments of each configuration significantly different?

   - Each segment statistically different aside from Program B between configurations A and B

   c. What is the difference between predicted and actual hours for each adjacent segment?

   - At least 20 thousand hours (usually under-estimated)

2. How many units of the newly configured aircraft are produced before the contractor regains the stable learning rate?

- Large sample size
  - In total
  - In each segment
- One configuration change
  - Isolated impact
- Stable slope: 63.26%
  - Configuration A
- Stabilized after 19 newly configured units

First Unit	Slope	Units to Stabilize
72	49.84%	
73	50.69%	1
74	51.34%	2
75	51.95%	3
76	52.48%	4
77	52.85%	5
78	52.83%	6
79	52.81%	7
80	53.21%	8
81	53.44%	9
82	53.80%	10
83	54.36%	11
84	54.85%	12
85	55.25%	13
86	56.33%	14
87	57.39%	15
88	59.18%	16
89	60.52%	17
90	62.03%	18
91	63.60%	19
92	64.36%	
93	64.30%	
94	64.52%	
95	63.51%	
96	62.06%	
97	60.54%	

Significance of Findings

- Configuration changes introduced during production may cause a statistically significant impact to the unit production learning rate and production hours

- After most of the configuration changes analyzed, the contractor achieved a steeper rate of learning than the stable rate
  - Analysis of Program A indicated the contractor's learning decreased with each subsequent production unit until eventually stabilizing

- In reality, a contractor will submit a tech-refresh proposal to program office to account for configuration change
  - Estimated based on extrapolation of stable learning curve

- In every program in this analysis (and in most segments), a newly configured aircraft initially experienced a higher rate of learning
  - An extrapolation of the stable curve will result in a higher per unit cost than the contractor would actually experience

The Impact of Learning Curve Model Selection and Criteria for Cost Estimation Accuracy in the DoD - Part 2

Background/Research Question

- Learning curves are commonly used in production estimates
  - Production accounts for the majority of total Acquisition Costs

- Mr. Thomas Henry (OSD CAPE) on modernization
  - "Manufacturing and depots are becoming as automated as possible. Learning curves could get much different in the future due to machines"

- Heightened scrutiny of cost estimates
  - Budget Control Act of 2011 seeks to reduce federal deficit

- Is the current DoD methodology is outdated? Are alternative models are more accurate?
  - Wright's original learning curve theory (CUMAV) was formulated in 1936.

Learning Theory

- T. P. Wright (1936) theorized that as a worker performs a task multiple times, the time required to complete that task will decrease at a *constant rate*.
  - Constant percentage decrease for doubling quantity
  - Wright's Learning Curve (WLC) Model:

$$y = ax^b$$

- Learning is a human phenomenon occurring in manual labor, so we should expect the most learning to occur when the production process involves a great deal of touch labor and little automation

- DeJong's Learning Formula
  - Incorporates percentage of process that is automated into learning models

- S-Curve Model
  - Incorporates prior experience units (prototypes) and percentage of process that is automated into learning curves.

Analytical Tests

- Use Historical data to determine CUMAV vs. Unit Theory
  - Use Regression statistics to determine validity of regression models

- Compare all sample means to determine if any models are different
  - Use skewness, kurtosis, and standard deviation to determine normality

- Compare sample means to determine which models are different from WLC status quo

- Compare means of S-Curve and DeJong if they are more accurate than WLC to determine the most accurate model

Data Table Example (WLC)

Unit (x)	Actual	Predicted	Error	Absolute Value Error	Absolute Value Percent Error
20	17336.81	17871.04	-534.22	534.22	0.03
21	17221.82	17721.17	-499.35	499.35	0.03
22	17041.33	17579.45	-538.12	538.12	0.03
23	16916.11	17445.09	-528.99	528.99	0.03
24	16854.60	17317.41	-462.81	462.81	0.03
25	16797.48	17195.83	-398.35	398.35	0.02
26	16710.27	17079.81	-369.54	369.54	0.02
27	16606.65	16968.92	-362.27	362.27	0.02

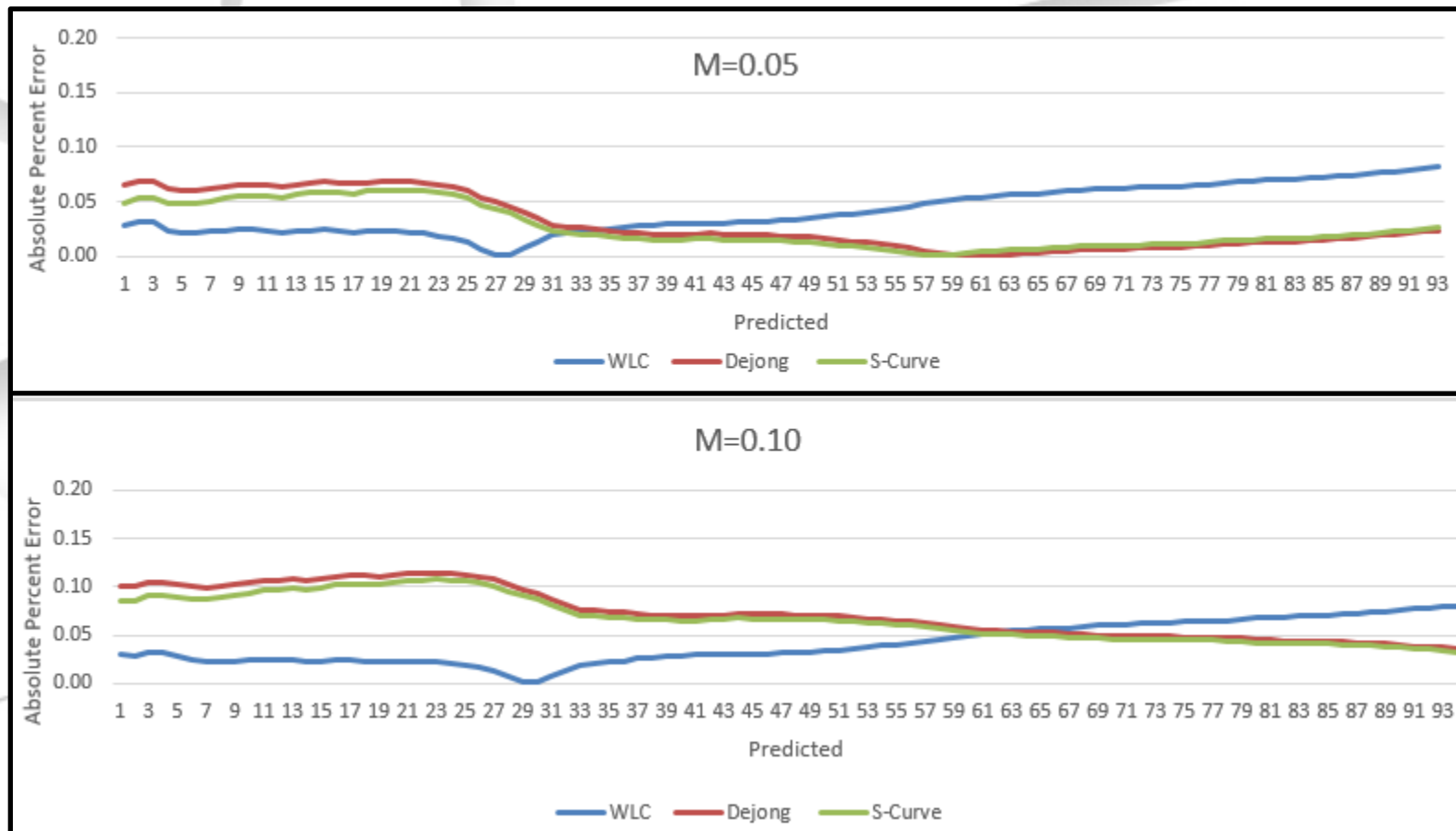- MAPE is the average of the Absolute Percent Error
- MAPES at M of 0.05
  - WLC = 4.11%
  - DeJong = 3.00%
  - S-Curve = 2.64%

Results: APE Graphs

Significance of Findings

- There is *potential* for a more accurate model in predicting the effects of learning within DoD acquisitions
    - S-Curve and DeJong models

- Sensitivity of results and uncertainty of incompressibility factor make it difficult to simplify the results

- Findings provide a proxy to future research and open a dialogue for change within DoD learning methodology

- The influence of machinery potentially displayed with long production cycle